US Industry-Level Returns and Oil Prices

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Abstract

This paper takes a closer look at the puzzle uncovered by Driesprong et al. (2008) and finds empirical support for the "oil effect" in equity returns. Using forty nine US industry-level returns series and changes in oil spot and future prices, we address whether industry-level returns are predictable. We find that using changes in oil spot prices, the answer is yes; but for just under a fifth of industries in our sample. We find weak support for the predictability of industry-level returns based on changes in oil future prices. Our findings are consistent with the delayed reaction to new information, a variant of Hong and Stein (1996)'s "underreaction" hypothesis.

Keywords: Industry-level returns, Oil prices, Return predictability, Underreaction.
JEL classification: G11, G14, and G17.

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1 Introduction

Driesprong et al. (2008) show that changes in oil prices can reasonably predict index returns of global financial markets. This interesting result deserves further investigation. It is necessary to know whether the returns of all industries in the index can be predicted by oil prices, or this phenomena is limited to a subset of constituent industries. While data for industry-level returns are not available for all markets studied by Driesprong et al. (2008), they are available for the US. In this study, using forty nine US industry-level portfolio return series, we extend and re-examine their findings to see whether oil prices can predict industry-level returns. We find that spot oil price changes have significant prediction power for slightly under one fifth of industry returns in our sample. Oil future prices have weak prediction power. Just three industry returns series can be predicted by oil future price changes. These results are robust with respect to a variety of alternative specifications. Our findings are in line with Hong and Stein (1996)'s "underreaction" hypothesis.

Predictability of stock returns has been seriously studied by academic financial economists since the 1980s. Predictability is an important subject, since a model with even very modest prediction power for asset returns can be used to generate significant profits. There are numerous studies that examine predictability based on valuation ratios or macroeconomic factors. Following the seminal work of Hamilton (1983) and the subsequent extensive research that this study generated, the economics profession accepts a link between oil prices and macroeconomic variables. Recent examples include Lee and Ni (2002), Hamilton (2003), Hamilton and Herrera (2004), Bachmeier et al. (2009), and Hamilton (2009), among others.[1] While many economists agree that oil prices and their fluctuations have significant impact on growth and business cycles, very few studies examine prediction power of oil prices for equity returns.

Influential studies of predictability of equity returns, based on valuation ratios, include Fama and French (1988), Campbell and Shiller (1988a), and Campbell and Shiller (1988b), among many others. Typical predictors used in this literature include dividend yields, price dividend ratios, and price earning ratios. These studies typically conclude that valuation ratios are positively correlated with subsequent returns and the implied predictability increases as prediction horizon becomes longer. Other studies consider the correlation between future stock returns and yields on short- and long-term treasury and corporate bonds. Important examples include Keim and Stambaugh (1986), Campbell (1987), and Fama and French (1989).

The impact of macroeconomic factors on stock market returns is studied in Chen et al. (1986). In this paper, the authors use a multifactor model which treats contemporaneous and/or leading innovations of various macroeconomic variables as factors. They want to find out whether priced-in

[1] Hooker (1996) argues that the oil price-macroeconomy relationship has changed and weakened in recent years.

factors such as industrial production and the unemployment rate can at least partially explain the unconditional cross-sectional distribution of expected returns. They specifically include monthly changes of the real price of oil in their analysis,[2] but find no evidence of a statistically significant relationship between unconditional returns and oil price changes. In a related study, Jagannathan and Wang (1996) consider the cross-section of unconditional expected returns, using factors such as the yield spread between Aaa and Baa rated bonds and the per capita growth rate of labor income. These factors explain a significant amount of the cross-sectional variation of expected returns. Campbell and Yogo (2006) report predictability with short rate and long-short yield spread as regressors.

There is a strong presumption in the financial press that oil prices strongly influence the stock market. But the empirical evidence on the impact of oil price fluctuations on stock prices are mixed. Jones and Kaul (1996) find that the reaction of United States and Canadian stock prices to oil shocks can be completely accounted for by the impact of these shocks on real cash flows alone. In contrast, in both the United Kingdom and Japan, innovations in oil prices appear to cause larger changes in stock prices than can be justified by subsequent changes in real cash flows or by changing expected returns. Kilian and Park (2009) find that the response of aggregate U.S. real stock returns may differ greatly depending on whether the increase in the price of crude oil is driven by demand or supply shocks in the crude market. In a study similar to Driesprong et al. (2008) and ours, Hong et al. (2007) test the predictability of aggregate market returns using returns for previous month from a variety of industries. Among other industries, they find that high returns for the petroleum industry predict lower returns for the US stock market.

Appealing to the gradual diffusion of information, or underreaction, literature pioneered by Hong and Stein (1996), Pollet (2004) investigates predictability of market returns and industry performance based on forecastable oil price movements. He believes that while predictability can be compatible with market efficiency, it may be more readily explained by underreaction to information about subsequent oil price changes. His study focuses on seemingly slow diffusion of information about anticipated oil price movements. In our study, we also address the "surprise" in oil price changes. Driesprong et al. (2008) also visit the underreaction issue. They claim that (p. 308) "the predictability effect is more pronounced in sectors where the economic impact of oil price changes is more difficult to infer. Oil sectors, or sectors in which the impact of oil prices is likely to be a dominant first-order effect, show less predictability." This is the heart of our contribution. We show, in detail, which US industries react to oil price changes, to what extent, and how.

The rest of the paper proceeds as follows: Section 2 describes and discusses the data. In Section 3, we introduce and discuss our findings regarding predictability of industry-level returns

[2] Their choice of oil price data, in our opinion, has some problems. We discuss this issue in our description of the data and choice of variables.

using oil prices, and perform robustness checks. We discuss underreaction of market participants with respect to oil prices in Section 4. In Section 5, we discuss the returns of an oil-based trading strategy and the relation between our findings and time varying risk premia. Section 6 concludes.

2 Data

2.1 Oil Price Data

The international oil market is the most active commodity market in the world. Driesprong et al. (2008) provide a concise, yet highly informative discussion of the international oil market, pricing conventions, contracts, and market characteristics. To save space we focus on results for West Texas Intermediate (WTI) crude oil. Unlike Driesprong et al. (2008), we do not report the results based on alternative spot prices such as North Sea Brent or Arab Light. WTI data is available for a longer time period, it is highly correlated with other oil spot price measures, and is more pertinent for a study of US industries. Nevertheless, our results are empirically robust across these different oil price series. We use WTI end of the month spot and contract number 1 Cushing, Oklahoma light sweet crude oil future prices from New York Mercantile Exchange (NYMEX) and reported by the US Department of Energy's Energy Information Administration (EIA). This data is also available from usual sources such as Thomson Datastream.

Summary statistics of these series are given in Table 1. Reported statistics pertain to "oil returns" processes, i.e. log differences in oil spot or future prices between two subsequent months. Average oil price changes and standard deviations are in percentages. These series demonstrate no unconditional skewness. On the other hand, based on reported excess Kurtosis, there is moderate unconditional leptokurtotic behavior present for both series.

Two influential papers, Hamilton (1983) and Chen et al. (1986), use wholesale oil price data collected by the Bureau of Labor Statistics. While this data might be useful for examining the relationship between quarterly changes in the price of oil and real GDP, it is very smooth and actually remains constant for three, four, and even five month periods during the mid 1970s and early 1980s (as late as 1984). This smoothness is misleading for empirical tests concerning monthly changes in oil prices and asset returns.

We justify using both spot and future prices data thus: we believe that spot prices reflect information available to the markets up to time t. This means that conditioning industry returns on lagged oil returns provides a semi-strong efficient prediction for industry returns. We believe that futures prices measure the sentiments of the market participants towards the short term future. Since oil markets are highly liquid, differences between oil spot and future prices are small, but non-negligible at each point in time. Thus we believe that conditioning industry returns on oil future price changes, measures the predictability content of market participants' sentiments towards the short term future.

2.2 US Industry-Level Returns

Industry level returns data is taken from Kenneth R. French's data bank.[3] We use average monthly value weighted returns on 49 industry level portfolios. The original data spans July 1926 to present. We use a subset of this data, from January 1979 to January 2009. There are 360 observations available for each returns series.

According to the data definitions, each NYSE, AMEX, and NASDAQ stock is assigned to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time. The data is constructed using Compustat SIC codes for the fiscal year ending in calendar year $t-1$. Whenever Compustat SIC codes are not available, CRSP SIC codes for June of year t are used. The monthly returns are then computed. Construction of this data bank ignores transaction costs and does not include a hold range.

Summary statistics are given in Table 2. Average sample returns and standard deviations are in percentages. None of the returns series exhibits heavy unconditional skewness. We report excess Kurtosis values in the table. Deviation from excess kurtosis greater than zero is seen in almost all industry return series. Based on sample statistics, we conclude that monthly returns demonstrate leptokurtotic behavior.

Welch and Goyal (2008) believe that many positive predictability results in the literature depend on samples which contain the oil shock of 1974. Our data starts in 1979, hence our results do not depend on, in the words of Welch and Goyal, this anomalous period.

3 Predictability of Industry-Level Returns

3.1 Basic Regression Model

We follow Driesprong et al. (2008) in testing the predictability of returns, instead of excess returns, for US industry portfolios. To test for the existence of an oil effect we incorporate an oil variable, $r_t^{oil,spot}$ or $r_t^{oil,future}$, in the regression

$$r_t^i = \mu_i + \alpha_i r_{t-1}^{oil,\cdot} + \varepsilon_t^i \qquad (1)$$

where r_t^i represents the returns of industry i at time t, μ_i's are real valued constants, $r_t^{oil,\cdot}$ denotes oil 'spot' or 'future' price changes, as discussed above. For simplicity, we do not indicate 'spot' or 'future' in the notation used for the parameters. The reported results in Tables are differentiated. ε_t^i are the usual error terms for each industry. In the absence of the oil variable, this

[3] This data set is available from `http://mba.tuck.dartmouth.edu/pages/ken.french/data_library.html`. Unfortunately, such detailed industry-level data is not available for other markets, developed or emerging, studied in Driesprong et al. (2008). Hence, we limit our study to the US industries.

equation reduces to the random walk model for log asset prices. We test whether the coefficient on $r_t^{oil,\cdot}$, α_i, is significantly different from zero for each industry. When α_i is significant, the null hypothesis of no oil effect is rejected. We estimate these regressions individually, since our objective is a study of prediction power of oil prices for each industry-level returns series. We estimate these regressions using ordinary least squares (OLS). As discussed earlier, industry returns and oil price changes series are leptokurtotic. Hence standard errors of the parameter estimates are not heteroskedasticity-consistent. We address this issue by using Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimators.[4]

3.2 Empirical Evidence

Estimated values of α_i parameters in Eq. (1) are reported in Panel A of Table 3. We report industry-returns which demonstrate statistically significant predictability for the sake of brevity. Oil spot price changes have prediction power for nine industry portfolio returns series. This translates to slightly less than 20% of industry-level returns in our sample. The null that these estimated parameters are not significantly different from zero is rejected at the 5% significance level for two industries, Meals with oil spot price changes and Retail with oil future price changes, and at the 10% significance level for two industries (Construction and Meals) using oil future price changes, and for eight industries (Autos, Boxes, Business Services, Construction, Personal Services, Retail, Rubber, and Telecom) using oil spot price changes. All in all, oil spot price changes can predict returns of nine out of forty nine industries in the US financial markets, or 18.36% of the total. Oil future price changes are far less successful. Using oil future price changes as predictor yields just three predictable industries.

All estimated parameters have a negative sign, which is in line with the findings of Driesprong et al. (2008). This implies that a positive change in oil price growth leads to a decline in industry-level returns in the subsequent month. The values of these estimated parameters range between a low of -0.05 for Telecom to a high of -0.088 for the Automotive industry, using oil spot price changes as predictor. If we use oil future price changes, these values range between -0.075 (Meals) to -0.095 (Construction). The estimated parameter for US index returns, using WTI price changes reported by Driesprong et al. (2008), is -0.086. In this respect, our estimates are closely in line with their finding.

Since industry returns are correlated, we also estimate the model as a system of seemingly unrelated regressions (SUR). Our interest is in testing jointly whether the hypothesis of $\alpha_i = 0$ is rejected for each industry. First, we find that joint estimation leads to a greater number of statistically significant prediction parameters for WTI spot price changes. Instead of nine predictable

[4]Driesprong et al. (2008) use the White (1980) estimator instead of the Newey-West estimator. The White estimator addresses heteroskedasticity, but it does not address serial correlation in the data.

industries, we now have nineteen, or approximately 39% of the industries in sample. All our initial predictable industries are in this subset. Moreover, banks, building materials, clothing, coal, finance, hardware and software, lab equipment, machinery, and textiles show signs of predictability using oil spot price changes as the predictor. All estimated parameters, whether statistically significant or not, have the expected negative sign, and their sizes closely follow the estimations of Driesprong et al. (2008). In fact, they range between -0.044 to -0.089. Second, we find Wald test statistics which indicate p-values smaller than 0.05. These findings confirm the evidence reported in Table 3. Our estimation results are robust to inclusion of returns from S&P 500 and Dow Jones Industrial Average indices.

Following the influential paper by Stambaugh (1999), many financial scholars have studied the problems of predictive regressions. A concise and lucidly written summary is given in Campbell and Yogo (2006). They also provide a pre-testing procedure for predictive regressions. We carry out these pre-tests and find that our formulation does not suffer from the overstatement of true significance by t-statistics which is documented in their study. These results are available upon request.

3.3 Robustness

We carry out robustness tests to address the following issues: robustness of prediction results with respect to contemporaneous correlation of oil price changes and equity returns, longevity of the oil effect, robustness to potential non-synchronous trading, and robustness to different specifications for oil price changes such as shocks in prices, non-linearities, and potential impact of lagged oil price changes on risk-return trade-off.

In the first step, we address whether the predictability results are due to contemporaneous correlation of oil price changes and equity returns. We simultaneously study the duration of the oil effect and robustness to potential non-synchronous trading. To examine these issues, we estimate the following regression model:

$$r_t^i = \mu_i + \alpha_{1,i} r_{t-1}^{oil} + \alpha_{2,i} r_{t-2}^{oil} + \alpha_{3,i} r_t^{oil} + \alpha_{4,i} r_{t-1}^i + \varepsilon_t^i. \tag{2}$$

In this model, inclusion of contemporaneous oil price changes controls for contemporaneous correlation between oil prices and industry-level returns. Similarly, industry-level returns lagged one month control for non-synchronous trading. By considering oil price changes lagged two months in addition to oil price changes lagged one month, we test for how long predictability effects last.[5] The results of regressing industry-level returns on individual variables besides oil price changes are

[5] Lag lengths of three, six, and twelve months where also studied. Since the results are very similar, they are not reported.

very similar, hence they are not reported.

Estimated results are reported in Table 4. We only report those industries which have at least one statistically significant estimated parameter. Estimated parameters are the output of OLS regression and all reported standard errors in are Newey-West HAC consistent estimates.

The top panel of Table 4 reports the results using changes in WTI spot prices. Eight industries show significant predictability. Two industries (retail and meals) lose predictability in presence of these additional explanatory variables. On the other hand, the building materials industry becomes predictable once lagged industry returns are included. Length of predictability period is quite short. Only one industry, construction, demonstrates statistically significant predictability using oil price changes at a two-month lag. We conclude that at industry-level returns, predictability does not extend beyond a one-month lag. Four industries, gold, mines, oil, and personal services, show evidence of contemporaneous correlation of oil and equity returns, through statistically significant parameters for contemporaneous oil returns. This is still quite low, just 8.16% of industries show signs of correlation between oil and industry returns. Moreover, such a relationship is not quite surprising for oil and mining industries. We expect information of oil prices to have a significant impact on oil and related industries' returns, but we also expect this information to be quickly absorbed and incorporated in the market prices.

Our findings here differ from Driesprong et al. (2008) in one important dimension. They find weak evidence of the importance of lagged index returns in their regression analysis. We, on the other hand, find a significant number of industries where lagged industry-level returns are significant predictors. This is suggestive, but is not conclusive evidence, of the presence of non-synchronous trading. Except for two industries, meals and retail, the inclusion of additional regressors hardly changes the value or significance of estimated one month lagged oil returns parameters. We conclude that predictability is fairly robust to inclusion of other factors.

The bottom panel of Table 4 reports the results using price changes in NYMEX light sweet crude future prices. These results are consistent with the conclusion in previous section that oil future price changes have weak prediction power for industry-level returns. By introduction of new variables in the prediction regression, we find that just two industries, hardware and personal services, show some level of predictability. The length of prediction life time is still very short. The coefficient of future price changes lagged two months is statistically significant for a single industry, oil. This result, especially for the oil industry where contemporaneous future price changes and lagged industry returns are also significant, is rather puzzling. Contemporaneous correlation between future price changes and industry-level returns are significant for six industries: food, drugs, gold, oil, personal services, retail, and meals. Similar to our findings using oil spot price changes, these results provide suggestive but inconclusive evidence of the presence of non-synchronous trading. Since introducing new factors does not change parameter estimates much,[6] we conclude that, while future price changes are not good predictors, the estimation results are reasonably robust to inclusion of other factors. We need to stress that we believe future prices do not posses much prediction power. In other words, market expectations seem to have little ability for predicting industry-level returns in the near future; all their relevant information is already incorporated in the stock prices.

We perform several additional robustness checks. To save space, we only report the main findings. As noted in the previous section, our results are based on industry-level returns. We also considered the model with excess returns, that is industry-level returns minus short term rates. We use the four week (one month) T-Bill rate as the short term risk free rate. We observe that the results are almost identical to those when we use returns instead of excess returns. Based on our empirical evidence, we believe that the formulation in Eq. (1) is robust to the use of either returns or excess returns.

A reasonable question is whether predictability is a results of anticipated component or an unanticipated news in oil returns. Pollet (2004) specifically studies anticipated oil price movements and their prediction power. Here we study the predictability content of unanticipated news. We have two measures for unanticipated news. The first measure is "oil shocks", which we construct by using the residuals of fitting the oil returns series using a first order autoregressive (AR(1)) process.[7] The intuition is to remove the easily predictable conditional mean component from oil spot or future price changes. We do not want to filter out the potentially present time varying volatility behavior, since we want to test whether these components convey news for the market. Second, we use "oil price volatility" which we construct by squaring oil price shocks. Volatility is a proxy for risk in these markets, and can also proxy for non-linearity in the oil-industry returns relationship.

Under alternative formulations for oil price impact, we substitute $r_t^{oil,\cdot}$ with measures for oil shocks or volatility as follows:

$$r_t^i = \mu_{i,s} + \alpha_{i,s} s_{t-1}^{oil,\cdot} + \varepsilon_t^{i,s} \tag{3}$$

$$r_t^i = \mu_{i,v} + \alpha_{i,v} v_{t-1}^{oil,\cdot} + \varepsilon_t^{i,v} \tag{4}$$

where oil shocks are denoted as $s_t^{oil,\cdot} = r_t^{oil,\cdot} - \hat{r}_t^{oil,\cdot}$ and $\hat{r}_t^{oil,\cdot}$ is the fitted value for oil price changes from an AR(1) process; oil volatility is denoted as $v_t^{oil,\cdot} = (s_t^{oil,\cdot})^2$. Values are calculated for both

[6]Introduction of these factors rendered three predictable industries unpredictable. Point and standard errors estimates for the rest, while statistically not significant, do not change much. These results are available upon request, but are not reported.

[7]We fit the oil return series using an ARMA(1,1) formulation too. Using the residuals from an ARMA(1,1) fit does not significantly change our findings.

spot and future prices. Similarly, $\mu_{i,\cdot}$, $\alpha_{i,\cdot}$, and $\varepsilon_t^{i,\cdot}$ pertain to either shock or volatility measures. The rest is identical to the oil price change prediction case.

Estimated values of $\alpha_{i,s}$ parameters in Eq. (3) are reported in Panel B of Table 3. A cursory look reveals that using the shock measure instead of price changes does not alter estimated values of parameters or their statistical significance. The same industry-level returns show evidence of predictability, and estimated parameters and standard errors are also very close to what is seen in Panel A. On the other hand, the prediction power of oil future price shocks is even less than that of oil future price changes reported in Panel A. A single industry returns series, construction, can be predicted and the size of the estimated parameter is visibly different from what is seen in Panel A. These findings reinforce our initial conclusion that oil spot price changes have more prediction power than oil future price changes. Moreover, we conclude that first, the prediction model is robust to use of price changes or shocks to oil spot returns, and second, we find evidence suggestive that the predictability stems from the unanticipated "news" contained in the oil price series.

The results from inclusion of volatility in prediction regression, Eq. (4), are very weak. Hence, we do not report the results, but briefly discuss the findings. We find that using oil spot volatility as the predictor, the null hypothesis that estimated $\alpha_{i,v}$ parameters are equal to zero is rejected at conventional confidence levels for only three industry-level series: agricultural products, wholesale, and real estate. A similar analysis using oil future price volatility similarly yields three predictable industry-level series. They are the aerospace, shipping, and insurance industries. All these estimated parameters have the expected negative sign. Since, using this measure, we can predict less than 10% of industry-level returns series in sample, we conclude that the constructed volatility measure used here does not have much prediction power for industry-level returns.

We explore the issue of volatility further and formally study the consequences of the inclusion of one month lagged oil price changes in risk-return trade-off at industry-level. Formally, we fitted a GARCH(1,1)-in-Mean model with oil prices lagged one month as an exogenous variable in the volatility process. In this respect, we follow French et al. (1987). This formulation allows us to explicitly check whether a lagged oil price change increases future industry-level volatility. We find out that the inclusion of oil price changes does not significantly alter the estimated parameters of the GARCH process or the value of the GARCH-in-Mean coefficient. The real estate industry has statistically significant estimated coefficients for both the GARCH-in-Mean term and the oil returns. But the sign of the GARCH-in-Mean coefficient is negative (-0.0791), which is counter intuitive, and only significant at the 10% significance level. This result implies that there is a negative relationship between risk and return, while we expect a positive relationship. All other results are both statistically insignificant and have negative GARCH-in-Mean parameters, hence we do not report them. We conclude that oil price changes do not alter the risk-return trade-off in the sample. Based on these results, it is possible to claim that predictability is not related to the time-varying risk premium. We discuss time-varying risk premia in detail in Section 5.2.

4 Underreaction to Oil Prices

Oil price information is both publicly available at no cost almost in real time and widely followed by the investors. Hence, it is interesting that such widely available information has predictability for a significant portion of US market stocks. At first glance, this observation may even be at odds with market efficiency. However, a rationality-consistent explanation is available through the gradual information diffusion hypothesis of Hong and Stein (1996). We examine the evidence supporting this hypothesis in the subsequent sections.

4.1 Underreaction and Oil Prices

The main assumption driving the Hong and Stein (1996) underreaction hypothesis is decision making by investors who are endowed with bounded rationality in presence of private information. As a result, and based on the additional assumption that private information diffuses gradually across investors who do not extract information from prices,[8] market prices react to information about fundamentals with a delay. The Hong and Stein (1996) framework can be extended to include underreaction in presence of publicly available information.

Hong et al. (2007) consider the scenario where the gradual diffusion of information across asset markets leads to cross-asset return predictability. The basic idea in their study is that some investors, for example those who specialize in trading the broad market index, receive information originating from certain industries, such as commercial real estate or commodities, with a lag.

We may infer that underreaction is possible in at least two cases in the presence of publicly and freely available data. The first case may occur when some investors find it difficult to evaluate the ramifications of existing or new information on equity values. Since market response to public information driven by the sum of private signals, lags in response, or inaction, may result in underreaction. The second case which, according to Hong et al. (2007), may lead to underreaction is when investors react to information at different points in time after it becomes available.

Information needs to have a meaningful impact on economic activity before it is captured by empirical analysis, as pointed out by both Hong et al. (2007) and Driesprong et al. (2008). Oil prices clearly have an impact on economic activity. It is reasonable to believe that industries such as petroleum or transportation have very accurate assessments of the first order effects of oil price changes. But as Hamilton (2003) shows, the precise second order effects of oil price changes on the economy are not well understood. As a result, the effects of changes in oil prices on stock prices are not quite clear. There may even be confusion about which source of information should be trusted. As we noted earlier (and as is discussed in Driesprong et al. (2008) as an example), many academic articles, including Chen et al. (1986) and more recently Hamilton (2003), are based

[8] They call them "newswatchers".

on the U.S. producer price index of oil. Oil price changes based on this index demonstrate up to three-month lags in movements compared to WTI spot price changes. Hence, if investors use different measures for oil price information, their actions will have very different outcomes which compare favorably with predictions of the underreaction hypothesis. In our study, we find evidence in favor of the hypothesis that investors may find it hard to analyze the information contained in oil price changes in industries which seem to be less oil-dependent, such as telecom or construction. We do have a puzzling outcome in our results. One expects the automotive industry to closely follow and immediately incorporate information contained in oil price data. But this is not the case. Oil price changes predict returns of automotive industry quite well. We believe that this, at first glance puzzling, result is due to difficulty of accurate assessment of secondary oil effects on profitability of the automotive industry. We believe that oil prices satisfy the criteria of Hong and Stein (1996) model. We empirically test the underreaction hypothesis, following Driesprong et al. (2008) steps.

4.2 Empirical Evidence

In this section, we carry out and report the results of Driesprong et al. (2008) "delayed reaction" test. The fundamental idea in this test is the Hong et al. (2007) assertion that investors may react to information with a delay, leading to underreaction. The test is developed through the following intuition: if investors "wake up" to new information with a delay, then the predictability effect should become stronger if one introduces small enough lags between monthly stock and lagged oil price changes. We expect the explanatory power of this regression to increase, due to capturing the delayed response up to a certain number of lags, and then to decline.

Since the duration of this delayed reaction to oil price changes is unknown, we try several lag lengths. In the first step, we assume that investors react to oil price changes a week (five trading days)[9] after a price movement. As a result, we expect that introducing a five trading day lag between monthly industry returns and oil price changes should increase the explanatory power of our regressions.

To carry out the testing process empirically, we construct a new monthly oil price series with delays of one and five trading days. WTI data is available on daily frequency from March 1986. Our sample is constructed by dropping the oil price changes of the last trading day (trading week) of the month $(t-1)$ and adding the oil price returns of the last trading day (trading week) of the previous month $(t-2)$. If the delayed reaction hypothesis holds, then the last price changes of the $t-2$ month should have more information content for predicting industry returns than the price changes on the last trading day (trading week) of the $t-1$ month.

[9]The choice of a trading week as the delayed reaction duration is arbitrary. The true duration may be shorter or longer. We test other lag lengths for robustness; see below.

The results are reported in Table 5. The top panel reports the regression results with no lags between the monthly industry-level returns and the monthly spot oil price changes of WTI. The middle and bottom panels in the table report the results for 1- and 5-trading day lags. Our findings are mixed, and resemble the results reported for Emerging Markets in the lower panel of Table 7 in Driesprong et al. (2008). We find that while the prediction of higher R^2 associated with longer lags holds for the construction industry, it does not hold for any other industry with statistically significant oil price change estimated parameters. However, we note that these drops in R^2 are negligible.

The choice of 1-trading day or one trading week (5-trading days) is arbitrary. We repeat the procedure for up to 11 trading days to avoid overlapping sample problems in estimation. Figure 1 plots the R^2 as a function of lags between the monthly industry-level returns and the monthly oil price changes for three of the industries with significant future and/or oil spot price impact parameters.[10] A pattern emerges across these plots: after an initial drop, the R^2 rises at around the 7^{th} or 8^{th} trading day lag, and then drops quickly again. With different magnitudes, this pattern is repeated across all industries. We believe that this pattern is supportive of a delayed reaction period of around 7 to 8 days long for a relatively large group of investors.

We also carry out weekly regressions to document the possibility of delayed reaction among investors using a different sampling frequency. The regression model used in this analysis is:

$$r_t^i = \mu_i + \alpha_{i,1} r_{t-1}^{oil} + \alpha_{i,2} r_{t-2}^{oil} + \alpha_{i,3} r_{t-3}^{oil} + \alpha_{i,4} r_{t-4}^{oil} + \alpha_{i,5} r_{t-5}^{oil} + \alpha_{i,6} r_{t-6}^{oil} + \alpha_{i,7} r_{t-7}^{oil} + \alpha_{i,8} r_{t-8}^{oil} + \varepsilon_t^i. \quad (5)$$

In this model, r_t^i represents returns of industry i portfolio, and r_{t-j}^{oil} represents changes in the WTI spot price, lagged j weeks. Naturally, the $\alpha_{i,j}$s represent the coefficient of changes in j-lagged oil prices for industry i. The reported standard errors are the Newey-West HAC consistent estimates. The regression analysis results are reported in Table 6. As is seen in the column Oil($t-1$), representative of a one-week lag in oil price changes, there is no predictability detectable. On the other hand, the column Oil($t-2$) reports almost universal predictability. This period corresponds to the 7 to 8 trading day delayed reaction in the market. We find this result particularly encouraging. Predictability disappears quickly. For lags of three to seven, evidence of predictability is very weak and it totally vanishes for Oil($t-8$). We take these results to be supportive of delayed reaction.

5 Financial and Economic Significance

Our findings are statistically significant. But do they convey any exploitable financial and economic information? Many anomalies documented in the financial literature can not be exploited, since they are "uncovered" through assuming away trading costs. Once trading costs are incorporated in

[10]The resulting plots are broadly similar for all industries, so we just report three representative examples.

the assessment of anomalies, they dominate any potential gains from active trading strategies based on the alleged anomaly. We carry out a simple exercise to compare the gains from an "oil strategy" and the benchmark "buy and hold" strategy in the presence of reasonable levels of trading costs.

Another issue is whether these predictability results are just byproducts of time varying risk premia. We have already provided a partial answer to this question in Section 3.3. We address the time-varying risk premium issue further in this section.

5.1 Economic Significance

We compare the performance of buy and hold and oil-based trading strategies returns in the presence of reasonable trading costs. Unless the oil-based trading strategy delivers a better performance than the buy and hold strategy, after subtraction of trading costs, it has no practical value. We find that the oil strategy indeed delivers superior performance for almost all industries in the sample. We take the following steps to construct the returns of the oil trading strategy. First, we take sixty observations from January 1979 to December 1983 for each industry. Thus, the sample period of comparison is January 1984 to December 2008. We estimate equation 1 using the initial 60 observations, then use the estimated parameters and the last observed oil price change to form a prediction for industry returns in the coming month.

We re-estimate the model every month using a sliding window of length sixty, and form one month ahead forecasts of industry returns as described above. We compare these forecast values with four week (one month) US T-Bill rates. If the expected return is higher than the T-Bill rate, we invest fully in the industry, otherwise we invest fully in T-Bills. We repeat this investment rule for every month. We assume switching costs equal to 0.10%. In this respect, we follow Solnik (1993) and Driesprong et al. (2008).

We thus construct oil strategy trading outcomes for each industry. These results are reported in Table 7. It is immediately obvious that the oil strategy delivers higher Sharpe ratios than the buy and hold strategy. Across all industries, the buy and hold strategy generates a return average of 10.67%.[11] These returns on average have standard deviation equal to 22.26%, with a maximum return obtained for Smoke (tobacco industry) equal to 17.83%, and a minimum return of -0.583 for real estate in this sample period. The average Sharpe ratio for this strategy is 0.478, with a maximum value of 0.845 for food and minimum value of -0.047 for real estate.

In contrast, the oil strategy delivers average returns of 12.92%. This translates to an improvement in returns equal to 2.25% compared with the buy and hold across all industries in our sample. The best return of the oil strategy is the software industry with 19.26% annual returns. The worst performance belongs to the real estate with 5.53% in annual returns. Notice that using the oil strategy, we could improve real estate's returns by 6.12%. The average standard deviation of re-

[11]This value is almost identical to the reported value in Driesprong et al. (2008).

turns of this strategy is 18.89% or an average risk reduction equal to 3.37%. In particular, the risk associated with the gold industry is reduced by 9.85% which we consider quite impressive. Even the smallest risk reduction, utilities, is still a respectable 1.05%. Average Sharpe ratio for oil strategy is 0.67 which translates to an average 0.19 improvement over buy and hold. As it is evident, this result is achieved through combined risk reduction and improved returns performance.

For the nine industries with strong evidence of oil-predictability in Table 3, average returns performance increases by 2.85%, average risk is reduced by 2.87%, and the average Sharpe ratio as a result increases from 0.487 to 0.721.

Our results are somewhat different from what Driesprong et al. (2008) report for the US. In their study, for a shorter sample and for MSCI index returns, the oil strategy outperforms buy and hold by 1.2% in average returns, reduces risk by 5.3%, and improves the Sharpe ratio from 0.39 to 0.72. In our exercise, the oil strategy delivers better average performance, but does not reduce risk as much. Still, it is clear that the oil strategy returns are superior to those of the buy and hold strategy.

An important issue which deserves attention is whether the risk free rate and market portfolio span the results of the oil strategy. Formally, we calculate Jensen's alpha from estimating the following model:

$$r_t^{os,i} - r_t^f = \alpha_i + \beta_i(r_t^m - r_t^f) + \varepsilon_t^i. \tag{6}$$

Here, $r_t^{os,i}$ are the returns from the oil strategy for industry i, r_t^m are market returns, and r_t^f is the risk-free rate. We use the four-week (one month) Treasury Bill rate as the risk-free rate and S&P 500 returns as the market returns proxies. Columns 8, 9, 17, and 18 in Table 7 report parameter estimates and t-statistics, in square brackets, based on Newey-West HAC consistent standard error estimates. As it is clearly seen in the table, the null hypothesis that Jensen's α ($\hat{\alpha}_i$) is equal to zero is frequently rejected. Since $\hat{\beta}_i$s are almost universally significant and reasonable,[12] we can say that mean-variance efficiency is rejected across industries. These results suffer from a slight look ahead bias: an oil effect exists and persists in the 1984 to 2008 period.

Again, our findings here differ from Driesprong et al. (2008) in one important dimension. We find that on average, a switch occurs every three to four months. Estimated Jensen's α for the US in Driesprong et al. (2008) is equal to 4.58% per year. Our estimated α's are much smaller; they range between 0.299% to 1.103%. Hence, while this strategy is profitable at transaction costs equal to 0.10%, profitability vanishes as transaction costs increase. This is contrary to what Driesprong et al. claim. Their results are said to be robust to transaction costs up to 0.5%.

In conclusion, we can say that first, the evidence for index market returns and risk-free rates

[12]Hardware, software, chip making, and finance industries have statistically significant estimated βs greater than unity. But these parameter values are close enough to one to suggest almost perfect cyclicality, an empirically acceptable regularity in these industries.

spanning of oil-strategy returns is weak. Second, oil strategy appears to be a reasonable trading rule for practitioners. Third, we conclude that there is evidence of an oil effect in the US industry-level returns.

5.2 Time Varying Risk Premia

We have already shown that oil price change related predictability is short-lived. As seen in Tables 4, 5, and 6, and contrary to Fama and French (1989), the oil effect does not last more than a month. This results is in line with findings of Driesprong et al. (2008). Fama and French (1989) argue that dividend yields, the term spread, and the default spread are reasonable variables for forecasting stock returns since they contain information about expected business conditions. Similarly, Chen et al. (1986) argue in favor of default spread as a good indicator for future business conditions. More recent examples include Ang and Bekaert (2007) who favor interest rates as predictors for equity returns, and Campbell and Thompson (2008) who favor a wide range of pricing ratios, among them interest rates, as well as term and default spreads.

As it is seen in Table 8, sample correlations between changes in WTI spot or future prices and US interest rates, term structure, or dividend yields are very close to zero. Correlation between changes in spot prices and the default spread is not negligible, but it is within the same order of magnitude as in Driesprong et al. (2008). These two sets of results are thus comparable and consistent. One may comfortably conclude that oil prices are linearly independent from accepted predicting variables for time-varying risk premia.

Also, as Hamilton (2003) documents, oil price shocks increase systemic risk in the economy. Such an event should be followed by increased expected (or average) returns across the industries. Our results demonstrate a negative relationship between oil prices and industry-level returns across the board, regardless of statistical significance. It can be argued that with time-varying risk premia, the contemporaneous effect of an increase in oil prices can be negative, due to uncertainty about short term profitability. But eventually, returns must rise if oil price changes are proxies for this phenomenon. Our econometric evidence rejects this assertion. We believe that the oil effect documented by Driesprong et al. (2008) and explored in our research does not proxy for time-varying risk premia and is a salient feature of the market.

In addition, a large body of literature in financial research starting with Merton (1980) is devoted to the study of the relationship between equity returns and risk. Merton's seminal paper argues that (excess) market returns should be directly and proportionally related to the market's systemic risk. Empirical study of this prediction underlies the extensive application of (G)ARCH-in-Mean models, starting with Engle et al. (1987), in the literature. As discussed in Section 3.3, if predictability from oil price changes is indeed related to time-varying risk premia, then we expect that inclusion of lagged oil price changes should improve the performance of GARCH-in-Mean regressions. Notice that our industry-level returns are portfolio returns, most of them consist of many companies.

Hence application of Merton's methodology is, in our opinion, valid. We find that first, there is no statistical evidence of improvement of fit. And second, the estimated coefficients do not have economically meaningful interpretations. Our estimated parameters for oil-in-volatility (exogenous parameter in GARCH process) are generally positive and indicative of increased volatility due to oil price changes. But except for very few industries, they are not statistically significant. We could not justify the assertion that inclusion of oil price changes improves the performance of the GARCH-in-Mean model based on econometric evidence. As a result, we believe that the main issue is independence of oil related predictability from time varying-risk premia.

6 Conclusions

We use disaggregated data to take a closer look at the "oil effect" documented by Driesprong et al. (2008). We use forty nine US industry-level return series and West Texas Intermediate spot and NYMEX light sweet crude future returns to verify the existence of predictability of stock returns, using oil price changes as predictors. Our findings provide two important refinements to the results of Driesprong et al. (2008). First, we identify which industries show oil-based predictability. Second, we show that the assertion by Driesprong et al. (2008) that underreaction stems from oil non-sensitive sectors can be empirically demonstrated. But we also find that there seems to be evidence that secondary oil effects render the automotive industry oil-predictable. Overall, our results provide important supporting evidence for both the "oil effect" and the underreaction hypothesis.

We find that industry-level returns in slightly less than twenty percent of the forty nine US industries studied in this paper can be predicted using logarithmic differences in West Texas Intermediate spot prices as predictor. Moreover, we find that this predictability almost disappears when we use logarithmic differences of NYMEX light sweet crude future prices.

Based on various robustness checks, we conclude that predictability is rather short lived, it is lost beyond a one-month lag. Less than 10% of industry-level returns demonstrate signs of contemporaneous correlation with oil returns. We find suggestive, but inconclusive, evidence of the presence of non-synchronous trading in a significant number of industry returns. Our results are robust to the use of excess returns, instead of raw returns, in the regression analysis. We find that the inclusion of oil price shock measures does not alter our findings, and that oil price volatility does not have much prediction power. In addition, we find that the oil effect seems to be independent of time-varying risk premia. Our findings differ in an important dimension from Driesprong et al. (2008). We show that gains from trading based on an "oil strategy" are sensitive to the size of trading costs. Existence of the oil effect seems to be a feature of US financial markets.

We find that our results are in line with the delayed reaction hypothesis among investors. In particular, by carrying out regression analysis between industry-level returns and lagged changes in monthly oil prices, we find an increase in explanatory power of these regressions, after an initial drop, at around seven to eight trading day lags. We interpret this results as a seven to eight trading day delay by a significant number of the investors. The delayed reaction is negative. This is consistent with the assertion that investors wake up to information at different points in time, as proposed by Hong and Stein (1996) and refined by Hong et al. (2007). Based on our findings, we believe that the investors underestimate the direct economic effect of oil price changes and take action with a non-negligible delay. We find that our results are more pronounced in non-oil related sectors such as construction and business services.

Comparison of predictability performance of oil price and valuation ratio based models is beyond the scope of the present paper. We will address this issue in future research.

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7 Tables

Table 1: Basic Characteristics of Oil Price Changes.

	Date	No. of Obs.	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis
WTI Spot Price	1979-01 : 2009-01	360	0.23	10.28	-0.70	4.77
NYMEX Future Price	1986-02 : 2009-01	275	0.10	10.27	-1.06	6.56

We report summary statistics for changes in West Texas Intermediate spot and NYMEX contract number 1 on Cushing, Oklahoma light sweet crude future oil prices. Oil price changes are defined as $r_t^{oil} = 100 \times [\ln(P_t^{oil} - \ln(P_{t-1}^{oil})]$. Average returns and standard deviations are reported as percentages. Excess Kurtosis values are reported. Source: Thomson Datastream and Energy Information Administration, US Department of Energy.

Table 2: Sample Statistics for Industry-Level Returns

Industry	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Industry	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis
Agric	1.22	5.98	-0.21	2.90	Guns	1.24	6.66	-0.32	3.25
Food	1.28	4.64	0.02	1.84	Gold	1.09	11.55	0.90	5.44
Soda	1.10	6.98	0.07	3.41	Mines	1.02	7.46	-0.64	2.69
Beer	1.45	5.42	-0.14	1.77	Coal	1.30	10.40	0.15	1.97
Smoke	1.56	6.87	-0.17	2.47	Oil	1.24	5.68	0.02	1.54
Toys	0.90	6.94	-0.44	1.83	Util	1.00	4.03	-0.34	0.63
Fun	1.11	7.11	-0.88	3.30	Telcm	0.90	5.09	-0.28	1.46
Books	0.87	5.47	-0.43	2.36	PerSv	0.97	6.02	-0.22	1.98
Hshld	1.05	4.61	-0.43	2.46	BusSv	0.99	5.60	-0.69	2.71
Clths	1.07	6.32	-0.54	2.76	Hardw	0.91	7.93	-0.28	1.72
Hlth	1.10	7.14	-0.24	1.52	Softw	1.53	9.09	0.25	0.67
MedEq	1.11	5.30	-0.51	1.71	Chips	1.08	8.14	-0.47	1.65
Drugs	1.21	4.94	-0.09	0.82	LabEq	0.97	7.47	-0.15	1.35
Chems	0.98	5.51	-0.54	3.13	Paper	0.93	5.49	-0.05	3.15
Rubbr	1.01	5.67	-0.72	3.14	Boxes	1.09	5.93	-0.63	2.74
Txtls	0.92	6.51	-0.97	3.97	Trans	1.03	5.66	-0.49	2.05
BldMt	1.00	5.83	-0.86	4.62	Whlsl	0.98	5.32	-0.59	3.54
Cnstr	1.12	7.29	-0.21	1.64	Rtail	1.20	5.62	-0.40	2.10
Steel	0.86	7.84	-0.42	2.76	Meals	1.10	5.43	-0.47	1.21
FabPr	0.48	7.13	-0.72	2.56	Banks	1.10	5.88	-0.55	1.93
Mach	0.88	6.41	-0.89	3.24	Insur	1.08	5.32	-0.49	2.96
ElcEq	1.31	6.29	-0.53	2.61	RlEst	0.39	6.35	-1.11	5.16
Autos	0.71	6.90	-0.68	3.14	Fin	1.25	6.45	-0.63	1.76
Aero	1.14	6.54	-0.60	3.08	Other	0.74	6.50	-0.40	1.49
Ships	0.94	7.03	-0.34	1.82					

Data spans January 1979 to January 2009 with 360 observations for each series. Industries are defined based on Compustat SIC codes when available, and CRSP SIC codes otherwise. Reported values are based on value-weighted industry portfolio returns, formed on July of each year, and revised at the end of the month of June of the subsequent year. Average returns and standard deviations are reported as percentages. Excess Kurtosis values are reported.
Source: Kenneth French's website.

Table 3: US Industry-Level Returns and Lagged Oil Price Changes

Panel A									
	Cnstr	Rtail	Meals	Rubbr	Autos	Telcm	PerSv	BusSv	Boxes
Oil Spot Price $\hat{\alpha}$	$-0.079^{\dagger}$ (0.046)	$-0.074^{\dagger}$ (0.040)	$-0.081^{\ddagger}$ (0.035)	$-0.070^{\dagger}$ (0.039)	$-0.088^{\dagger}$ (0.046)	$-0.050^{\dagger}$ (0.030)	$-0.063^{\dagger}$ (0.035)	$-0.064^{\dagger}$ (0.037)	$-0.066^{\dagger}$ (0.033)
Oil Future Price $\hat{\alpha}$	$-0.095^{\dagger}$ (0.053)	$-0.080^{\ddagger}$ (0.040)	$-0.075^{\dagger}$ (0.045)						

Panel B									
	Cnstr	Rtail	Meals	Rubbr	Autos	Telcm	PerSv	BusSv	Boxes
Oil Spot Price Shock $\hat{\alpha}_s$	$-0.075^{\dagger}$ (0.045)	$-0.073^{\dagger}$ (0.040)	$-0.079^{\ddagger}$ (0.035)	$-0.070^{\dagger}$ (0.039)	$-0.087^{\dagger}$ (0.046)	$-0.051^{\dagger}$ (0.030)	$-0.063^{\dagger}$ (0.034)	$-0.063^{\dagger}$ (0.037)	$-0.065^{\dagger}$ (0.034)
Oil Future Price Shock $\hat{\alpha}_s$	$-0.081^{\ddagger}$ (0.041)								

Notes: Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the parameter equals zero at the 5%, and 10% significance levels, respectively. The estimated parameters were obtained by applying OLS to $r_t^i = \mu_i + \alpha_i r_{t-1}^{oil,\cdot} + \varepsilon_t^i$. Sample length for spot oil price covers January 1979 to December 2008 period. Our sample for future oil prices covers January 1986 to December 2008 period.

Table 4: Robustness Checks

Spot Oil Price					Spot Oil Price				
Industry	Oil(t-1)	Oil(t-2)	Oil(t)	r(t-1)	Industry	Oil(t-1)	Oil(t-2)	Oil(t)	r(t-1)
Fun	−0.028 (0.052)	0.006 (0.037)	−0.026 (0.058)	$0.166^{\ddagger}$ (0.066)	Gold	−0.007 (0.061)	−0.093 (0.071)	$0.177^{\ddagger}$ (0.065)	−0.027 (0.062)
Books	−0.018 (0.036)	−0.009 (0.027)	−0.016 (0.049)	$0.191^{\ddagger}$ (0.077)	Mines	−0.044 (0.036)	−0.053 (0.037)	$0.106^{\ddagger}$ (0.053)	0.046 (0.075)
Clths	−0.062 (0.044)	0.015 (0.030)	−0.063 (0.055)	$0.205^{\ddagger}$ (0.062)	Oil	0.001 (0.027)	−0.038 (0.025)	$0.162^{\ddagger}$ (0.035)	−0.063 (0.059)
Hlth	0.026 (0.047)	0.018 (0.036)	−0.025 (0.041)	$0.132^{\ddagger}$ (0.049)	Telcm	$-0.050^{\dagger}$ (0.030)	0.008 (0.025)	−0.002 (0.036)	0.066 (0.048)
Rubbr	$-0.068^{\dagger}$ (0.037)	0.002 (0.029)	−0.009 (0.047)	0.068 (0.061)	PerSv	−0.049 (0.031)	0.009 (0.029)	$-0.066^{\dagger}$ (0.036)	$0.114^{\ddagger}$ (0.046)
Txtls	−0.051 (0.055)	−0.017 (0.028)	−0.063 (0.051)	$0.228^{\ddagger}$ (0.050)	BusSv	$-0.065^{\ddagger}$ (0.033)	−0.018 (0.027)	0.015 (0.041)	$0.130^{\ddagger}$ (0.052)
BldMt	$-0.057^{\dagger}$ (0.034)	−0.025 (0.027)	−0.003 (0.061)	$0.100^{\dagger}$ (0.051)	Boxes	$-0.061^{\dagger}$ (0.034)	0.004 (0.027)	−0.039 (0.043)	0.064 (0.062)
Cnstr	$-0.081^{\ddagger}$ (0.040)	$-0.054^{\dagger}$ (0.033)	0.015 (0.051)	$0.165^{\ddagger}$ (0.051)	Whlsl	−0.009 (0.030)	−0.005 (0.024)	−0.014 (0.041)	$0.127^{\ddagger}$ (0.059)
FabPr	−0.026 (0.057)	0.049 (0.037)	0.050 (0.056)	$0.171^{\ddagger}$ (0.068)	Rtail	−0.059 (0.038)	0.011 (0.029)	−0.064 (0.043)	$0.141^{\ddagger}$ (0.065)
Mach	$-0.071^{\dagger}$ (0.043)	0.010 (0.030)	0.050 (0.053)	$0.133^{\ddagger}$ (0.066)	Meals	−0.069 (0.033)	−0.024 (0.026)	−0.056 (0.038)	0.129 (0.050)
Autos	$-0.084^{\ddagger}$ (0.040)	−0.001 (0.036)	−0.015 (0.070)	$0.132^{\ddagger}$ (0.056)	RlEst	−0.050 (0.042)	0.002 (0.032)	−0.021 (0.055)	$0.330^{\ddagger}$ (0.058)
Aero	−0.039 (0.041)	−0.007 (0.029)	−0.020 (0.047)	$0.107^{\ddagger}$ (0.050)	Fin	−0.057 (0.048)	0.013 (0.030)	−0.022 (0.051)	$0.165^{\ddagger}$ (0.067)
Ships	−0.033 (0.051)	−0.026 (0.037)	−0.016 (0.042)	$0.093^{\dagger}$ (0.054)					
Future Oil Price					Future Oil Price				
Industry	Oil(t-1)	Oil(t-2)	Oil(t)	r(t-1)	Industry	Oil(t-1)	Oil(t-2)	Oil(t)	r(t-1)
Food	0.042 (0.032)	−0.028 (0.026)	$-0.080^{\ddagger}$ (0.038)	0.045 (0.069)	Ships	−0.010 (0.064)	−0.041 (0.036)	−0.008 (0.043)	$0.145^{\ddagger}$ (0.059)
Fun	−0.032 (0.063)	0.011 (0.043)	−0.028 (0.063)	$0.211^{\ddagger}$ (0.072)	Gold	−0.031 (0.063)	−0.100 (0.074)	$0.235^{\ddagger}$ (0.074)	−0.102 (0.066)
Books	0.001 (0.041)	−0.028 (0.035)	−0.015 (0.056)	$0.167^{\dagger}$ (0.092)	Oil	0.005 (0.031)	$-0.050^{\dagger}$ (0.029)	$0.172^{\ddagger}$ (0.043)	−0.107 (0.081)
Clths	−0.030 (0.058)	−0.010 (0.041)	−0.076 (0.059)	$0.205^{\ddagger}$ (0.067)	PerSv	$-0.060^{\dagger}$ (0.036)	0.022 (0.031)	$-0.074^{\dagger}$ (0.039)	$0.113^{\ddagger}$ (0.053)
Hlth	0.064 (0.053)	−0.015 (0.035)	−0.048 (0.046)	$0.121^{\ddagger}$ (0.061)	BusSv	−0.062 (0.041)	−0.007 (0.031)	−0.005 (0.048)	$0.116^{\dagger}$ (0.062)
Drugs	0.025 (0.037)	−0.024 (0.029)	$-0.091^{\ddagger}$ (0.037)	0.031 (0.074)	Hardw	$-0.102^{\dagger}$ (0.060)	0.074 (0.052)	0.019 (0.054)	0.058 (0.059)
Txtls	−0.030 (0.068)	0.004 (0.039)	−0.084 (0.057)	$0.247^{\ddagger}$ (0.052)	Whlsl	0.012 (0.035)	−0.018 (0.026)	−0.026 (0.047)	$0.139^{\dagger}$ (0.070)
Cnstr	−0.080 (0.050)	−0.054 (0.036)	−0.003 (0.060)	$0.126^{\dagger}$ (0.067)	Rtail	−0.036 (0.050)	−0.004 (0.041)	$-0.088^{\dagger}$ (0.046)	0.111 (0.079)
FabPr	−0.040 (0.065)	0.066 (0.042)	0.056 (0.066)	$0.184^{\ddagger}$ (0.080)	Meals	−0.048 (0.041)	−0.034 (0.026)	$-0.072^{\dagger}$ (0.039)	$0.127^{\ddagger}$ (0.060)
Mach	−0.071 (0.053)	0.033 (0.035)	0.051 (0.061)	$0.144^{\dagger}$ (0.076)	RlEst	−0.039 (0.055)	−0.029 (0.032)	−0.027 (0.064)	$0.352^{\ddagger}$ (0.061)
Autos	−0.051 (0.058)	0.010 (0.042)	−0.034 (0.078)	$0.134^{\ddagger}$ (0.058)	Fin	−0.039 (0.058)	0.007 (0.036)	−0.044 (0.058)	$0.161^{\ddagger}$ (0.074)
Aero	−0.004 (0.046)	−0.010 (0.029)	−0.028 (0.049)	$0.117^{\dagger}$ (0.061)					

Notes: Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the parameter equals zero at the 5%, and 10% significance levels, respectively. The estimated parameters were obtained by applying OLS to $r_t^i = \mu_i + \alpha_{i,1} r_{t-1}^{oil} + \alpha_{i,2} r_{t-2}^{oil} + \alpha_{i,3} r_t^{oil} + \alpha_{i,4} r_{t-1} + \varepsilon_t^i$. Our measure for oil price changes is returns to West Texas Intermediate spot and NYMEX light sweet crude future prices. Sample length for spot oil price covers January 1979 to December 2008 period. Our sample for future oil prices covers January 1986 to December 2008 period.

Table 5: Regression results with different lags between stock returns and lagged oil price changes.

	No Lag				No Lag		
Industry	Coeff.	Std. Err.	R^2 (%)	Industry	Coeff.	Std. Err.	R^2 (%)
Cnstr	$-2.546^{\ddagger}$	1.179	2.85	Hardw	$-2.223^{\dagger}$	1.263	1.45
Autos	$-2.122^{\dagger}$	1.277	1.85	Softw	$-2.939^{\ddagger}$	1.414	2.54
Telcm	$-1.593^{\ddagger}$	0.788	1.88	Chips	$-2.662^{\dagger}$	1.421	2.01
PerSv	$-2.099^{\ddagger}$	0.835	2.64	Rtail	$-1.829^{\dagger}$	0.958	2.23
BusSv	$-1.882^{\ddagger}$	0.863	2.58	Meals	$-2.528^{\ddagger}$	0.853	4.75
	One Day Lag				One Day Lag		
Industry	Coeff.	Std. Err.	R^2 (%)	Industry	Coeff.	Std. Err.	R^2 (%)
Cnstr	$-2.713^{\ddagger}$	1.225	3.29	Softw	$-2.659^{\dagger}$	1.542	2.12
Telcm	$-1.505^{\dagger}$	0.888	1.71	Rtail	$-1.782^{\dagger}$	0.972	2.16
PerSv	$-1.923^{\ddagger}$	0.813	2.26	Meals	$-2.187^{\ddagger}$	0.832	3.62
BusSv	$-1.711^{\dagger}$	0.944	2.17				
	Five Day Lag				Five Day Lag		
Industry	Coeff.	Std. Err.	R^2 (%)	Industry	Coeff.	Std. Err.	R^2 (%)
Autos	$-1.896^{\dagger}$	1.095	1.70	BusSv	$-1.520^{\dagger}$	0.874	1.94
Coal	$2.907^{\dagger}$	1.701	1.69	Rtail	$-1.608^{\dagger}$	0.970	1.99
Telcm	$-1.339^{\dagger}$	0.752	1.53	Meals	$-1.824^{\ddagger}$	0.847	2.85
PerSv	$-1.533^{\dagger}$	0.789	1.62				

Notes: Estimation results of regression equation $r_t^i = \mu_i + \alpha_i r_{t-1}^{oil} + \varepsilon_t^i$ with lags of a different number of trading days between monthly stock market returns and lagged monthly oil price changes. We report results for West Texas Intermediate spot oil price changes over the period March 1986-December 2008, with lags of 0,1,and 5 trading days. Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the β_i parameter equals zero at the 5%, and 10% significance levels, respectively.

Table 6: Weekly Predictability Results

Ind.	Oil(-1)	Oil(-2)	Oil(-3)	Oil(-4)	Oil(-5)	Oil(-6)	Oil(-7)	Oil(-8)
Agric	−0.005 (0.005)	−0.012‡ (0.004)	0.003 (0.005)	−0.004 (0.005)	0.002 (0.006)	0.007† (0.004)	−0.001 (0.005)	−0.002 (0.005)
Food	0.001 (0.004)	−0.007† (0.004)	−0.001 (0.004)	−0.004 (0.004)	−0.002 (0.004)	0.002 (0.003)	0.003 (0.003)	0.004 (0.003)
Beer	0.003 (0.005)	−0.012‡ (0.005)	−0.001 (0.005)	−0.005 (0.004)	0.000 (0.005)	0.003 (0.004)	0.000 (0.004)	0.008‡ (0.004)
Smoke	0.006 (0.005)	−0.009 (0.007)	−0.004 (0.006)	0.005 (0.006)	−0.013‡ (0.007)	0.000 (0.005)	0.003 (0.006)	0.004 (0.005)
Toys	−0.004 (0.005)	−0.013‡ (0.005)	0.003 (0.006)	0.004 (0.005)	−0.002 (0.006)	0.005 (0.004)	−0.010‡ (0.005)	−0.006 (0.006)
Fun	−0.004 (0.006)	−0.013‡ (0.006)	0.006 (0.007)	−0.006 (0.007)	−0.001 (0.012)	−0.005 (0.006)	0.002 (0.005)	−0.003 (0.008)
Books	0.000 (0.005)	−0.013‡ (0.004)	0.004 (0.005)	−0.005 (0.004)	0.002 (0.007)	0.001 (0.004)	0.000 (0.004)	−0.003 (0.006)
Hshld	0.001 (0.004)	−0.011‡ (0.004)	−0.001 (0.004)	0.001 (0.004)	−0.003 (0.005)	0.005 (0.003)	−0.001 (0.004)	0.002 (0.003)
Clths	−0.004 (0.005)	−0.011‡ (0.005)	−0.001 (0.006)	−0.004 (0.005)	0.001 (0.007)	−0.004 (0.005)	−0.001 (0.004)	−0.008† (0.005)
MedEq	0.003 (0.004)	−0.008† (0.005)	−0.004 (0.005)	−0.002 (0.004)	−0.005 (0.006)	0.006† (0.004)	0.003 (0.004)	0.001 (0.004)
Chems	0.000 (0.004)	−0.011‡ (0.005)	0.006 (0.005)	0.000 (0.004)	0.000 (0.006)	0.001 (0.004)	0.002 (0.004)	0.003 (0.005)
Rubbr	−0.001 (0.004)	−0.012‡ (0.004)	−0.001 (0.004)	0.001 (0.004)	−0.002 (0.005)	−0.004 (0.004)	0.000 (0.004)	−0.004 (0.005)
Txtls	−0.004 (0.005)	−0.017‡ (0.006)	0.002 (0.006)	−0.007 (0.005)	0.002 (0.008)	−0.005 (0.005)	0.000 (0.005)	−0.005 (0.007)
BldMt	−0.001 (0.005)	−0.013‡ (0.004)	0.002 (0.005)	0.001 (0.004)	−0.003 (0.005)	−0.002 (0.004)	−0.004 (0.004)	−0.004 (0.005)
Cnstr	−0.003 (0.006)	−0.023‡ (0.006)	0.004 (0.006)	−0.002 (0.006)	−0.005 (0.008)	−0.006 (0.006)	−0.004 (0.005)	−0.010 (0.009)
Steel	−0.002 (0.008)	−0.013‡ (0.006)	0.005 (0.007)	0.001 (0.006)	−0.005 (0.008)	−0.001 (0.006)	−0.002 (0.006)	−0.006 (0.008)
FabPr	−0.002 (0.005)	−0.011‡ (0.005)	0.003 (0.007)	−0.003 (0.006)	−0.002 (0.007)	0.008 (0.005)	0.004 (0.006)	−0.002 (0.006)
Mach	−0.001 (0.005)	−0.016‡ (0.004)	0.006 (0.006)	−0.006 (0.005)	−0.001 (0.007)	0.001 (0.004)	−0.003 (0.004)	0.000 (0.005)
ElcEq	−0.001 (0.005)	−0.014‡ (0.005)	0.004 (0.006)	−0.007 (0.005)	−0.005 (0.006)	0.001 (0.005)	−0.002 (0.004)	0.004 (0.005)
Autos	0.001 (0.006)	−0.020‡ (0.005)	0.004 (0.007)	−0.009 (0.005)	−0.001 (0.007)	−0.005 (0.005)	−0.002 (0.005)	−0.002 (0.006)
Ships	0.003 (0.005)	−0.014‡ (0.005)	−0.003 (0.005)	−0.003 (0.005)	−0.001 (0.005)	−0.001 (0.004)	0.004 (0.004)	−0.004 (0.004)
Guns	0.003 (0.006)	−0.008†) (0.005)	−0.001 (0.006)	0.001 (0.005)	0.002 (0.006)	0.003) (0.005)	0.000 (0.005)	−0.003 (0.004)

Ind.	Oil(-1)	Oil(-2)	Oil(-3)	Oil(-4)	Oil(-5)	Oil(-6)	Oil(-7)	Oil(-8)
Mines	−0.005 (0.007)	−0.010‡ (0.005)	0.005 (0.006)	−0.006 (0.005)	−0.003 (0.007)	−0.011‡ (0.005)	0.006 (0.005)	−0.007 (0.008)
Coal	−0.010 (0.009)	−0.015‡ (0.007)	0.013 (0.011)	−0.009 (0.008)	0.011 (0.010)	0.000 (0.007)	0.008 (0.007)	−0.012 (0.010)
Oil	−0.004 (0.005)	−0.014‡ (0.007)	0.005 (0.005)	0.005 (0.004)	−0.001 (0.005)	−0.001 (0.004)	−0.001 (0.004)	−0.003 (0.004)
Util	0.002 (0.003)	−0.011‡ (0.005)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)	−0.001 (0.003)	0.000 (0.003)	0.000 (0.003)
Telcm	0.002 (0.004)	−0.010† (0.005)	0.005 (0.005)	−0.007 (0.004)	−0.007 (0.005)	0.000 (0.004)	0.002 (0.004)	−0.002 (0.005)
PerSv	−0.007 (0.005)	−0.011‡ (0.005)	−0.003 (0.005)	−0.004 (0.004)	−0.003 (0.007)	0.000 (0.004)	0.001 (0.004)	−0.003 (0.005)
BusSv	0.001 (0.004)	−0.011‡ (0.004)	0.006 (0.005)	−0.007† (0.004)	−0.007 (0.006)	−0.001 (0.004)	−0.004 (0.004)	−0.002 (0.004)
Hardw	0.001 (0.007)	−0.011† (0.006)	0.010 (0.006)	−0.006 (0.006)	−0.005 (0.007)	0.002 (0.006)	−0.010† (0.006)	0.007 (0.006)
Softw	0.002 (0.006)	−0.010† (0.006)	0.010 (0.006)	−0.008 (0.005)	−0.012† (0.006)	0.000 (0.006)	−0.007 (0.005)	0.005 (0.006)
Chips	0.003 (0.006)	−0.014‡ (0.006)	−0.011† (0.006)	−0.014‡ (0.006)	−0.007 (0.007)	0.004 (0.006)	−0.012‡ (0.006)	0.005 (0.006)
LabEq	0.003 (0.005)	−0.09 (0.006)	0.009 (0.006)	−0.006 (0.005)	−0.006 (0.006)	0.007 (0.006)	−0.009† (0.005)	−0.001 (0.005)
Paper	−0.001 (0.004)	−0.011‡ (0.004)	0.003 (0.004)	0.001 (0.004)	0.000 (0.005)	0.001 (0.004)	0.003 (0.004)	0.000 (0.004)
Boxes	−0.006 (0.005)	−0.013‡ (0.004)	0.002 (0.005)	−0.005 (0.004)	−0.001 (0.006)	−0.001 (0.005)	−0.004 (0.004)	0.001 (0.005)
Trans	−0.003 (0.004)	−0.012‡ (0.004)	0.002 (0.004)	−0.005 (0.004)	−0.002 (0.005)	0.002 (0.004)	−0.002 (0.004)	0.001 (0.004)
Whlsl	−0.002 (0.004)	−0.010‡ (0.004)	0.004 (0.005)	0.001 (0.004)	−0.002 (0.005)	0.001 (0.003)	−0.002 (0.003)	0.000 (0.004)
Rtail	0.000 (0.005)	−0.014‡ (0.004)	0.004 (0.005)	−0.005 (0.004)	−0.006 (0.006)	0.003 (0.004)	−0.006 (0.004)	0.002 (0.005)
Meals	−0.002 (0.004)	−0.015‡ (0.004)	0.000 (0.004)	−0.009‡ (0.004)	−0.005 (0.005)	−0.001 (0.004)	−0.001 (0.004)	0.001 (0.004)
Banks	−0.002 (0.005)	−0.014‡ (0.006)	0.004 (0.006)	−0.005 (0.005)	−0.001 (0.007)	−0.004 (0.005)	0.000 (0.005)	−0.009 (0.008)
Insur	−0.003 (0.004)	−0.015‡ (0.006)	0.002 (0.006)	−0.002 (0.004)	−0.004 (0.005)	0.001 (0.004)	0.003 (0.004)	−0.004 (0.006)
RlEst	−0.004 (0.005)	−0.010‡ (0.005)	0.001 (0.005)	−0.004 (0.005)	−0.001 (0.009)	−0.007† (0.004)	−0.007 (0.004)	−0.006 (0.007)
Fin	0.001 (0.006)	−0.018‡ (0.006)	0.014† (0.008)	−0.011† (0.006)	−0.006 (0.008)	−0.003 (0.006)	−0.004 (0.005)	−0.004 (0.007)
Other	−0.002 (0.005)	−0.007† (0.004)	0.004 (0.005)	−0.007 (0.005)	−0.005 (0.006)	−0.001 (0.004)	0.000 (0.004)	0.001 (0.005)

Notes: Estimation results of regression Eq. (5): $r_t^i = \mu_i + \alpha_{i,1} r_{t-1}^{oil} + \alpha_{i,2} r_{t-2}^{oil} + \alpha_{i,3} r_{t-3}^{oil} + \alpha_{i,4} r_{t-4}^{oil} + \alpha_{i,5} r_{t-5}^{oil} + \alpha_{i,6} r_{t-6}^{oil} + \alpha_{i,7} r_{t-7}^{oil} + \alpha_{i,8} r_{t-8}^{oil} + \varepsilon_t^i$ using weekly data. We report results for West Texas Intermediate spot oil price changes over the period March 1986-December 2008, with lags of 1, 2, 3, 4, 5, 6, 7, and 8 trading weeks. Newey-West HAC consistent standard errors appear in parentheses. ‡, and † denote rejection of the null hypothesis that the $\beta_{i,j}$ parameter equals zero at the 5%, and 10% significance levels, respectively.

Table 7: Economic significance of the oil strategy

	Buy and Hold Strategy			Oil Strategy						Buy and Hold Strategy			Oil Strategy				
Industry	Mean	Std. Dev.	S.R.	Mean	Std. Dev.	S.R.	$\hat{\alpha}$	$\hat{\beta}$	Industry	Mean	Std. Dev.	S.R.	Mean	Std. Dev.	S.R.	$\hat{\alpha}$	$\hat{\beta}$
Agric	13.03	20.53	0.615	15.34	18.78	0.796	1.073‡ [3.747]	0.581‡ [5.551]	Guns	12.74	22.14	0.557	12.32	18.52	0.644	0.813‡ [2.747]	0.475‡ [4.429]
Food	14.35	16.50	0.845	13.03	15.75	0.802	0.856‡ [3.132]	0.512‡ [5.764]	Gold	8.269	38.02	0.207	15.03	28.17	0.519	1.103‡ [3.087]	0.334‡ [2.607]
Soda	12.82	25.41	0.489	12.30	22.83	0.522	0.752‡ [2.197]	0.610‡ [4.464]	Mines	11.42	25.28	0.290	13.68	21.53	0.617	0.832‡ [2.751]	0.686‡ [6.983]
Beer	15.52	18.88	0.801	14.67	17.27	0.826	0.977‡ [3.607]	0.547‡ [5.377]	Coal	16.10	37.13	0.423	19.20	30.17	0.623	1.402‡ [2.644]	0.440‡ [3.336]
Smoke	17.83	25.04	0.696	13.82	21.77	0.617	0.915‡ [2.428]	0.527‡ [4.903]	Oil	13.77	18.17	0.736	13.80	17.06	0.786	0.899‡ [3.860]	0.559‡ [7.759]
Toys	7.541	23.72	0.301	13.35	17.35	0.747	0.866‡ [3.118]	0.550‡ [5.818]	Util	11.07	14.13	0.755	11.26	13.08	0.831	0.796‡ [3.799]	0.316‡ [4.762]
Fun	12.22	24.85	0.476	14.29	21.13	0.658	0.764‡ [2.409]	0.952‡ [8.694]	Telcm	10.03	18.38	0.524	13.54	15.80	0.832	0.825‡ [3.214]	0.675‡ [9.143]
Books	7.214	18.78	0.363	12.27	16.11	0.737	0.684‡ [3.389]	0.755‡ [8.253]	PerSv	9.002	20.72	0.415	12.32	18.13	0.658	0.703‡ [2.528]	0.722‡ [6.101]
Hshld	11.89	16.05	0.716	11.67	14.70	0.767	0.708‡ [3.112]	0.588‡ [6.668]	BusSv	8.723	18.80	0.443	11.14	16.25	0.661	0.558‡ [2.705]	0.825‡ [8.541]
Clths	9.819	22.37	0.421	10.96	18.72	0.564	0.566‡ [1.808]	0.774‡ [6.592]	Hardw	10.14	28.73	0.339	13.95	25.10	0.540	0.691‡ [1.722]	1.049‡ [7.578]
Hlth	8.590	23.59	0.347	10.64	17.88	0.573	0.660‡ [2.239]	0.503‡ [4.873]	Softw	13.71	29.77	0.447	19.26	26.37	0.715	1.101‡ [2.688]	1.124‡ [7.298]
MedEq	12.41	18.40	0.652	12.94	16.77	0.748	0.754‡ [3.215]	0.723‡ [8.069]	Chips	10.86	29.30	0.357	15.83	25.00	0.617	0.851‡ [2.244]	1.044‡ [6.568]
Drugs	14.15	17.63	0.780	12.72	16.50	0.747	0.769‡ [3.170]	0.649‡ [7.574]	LabEq	8.599	25.37	0.323	13.81	20.49	0.655	0.780‡ [2.481]	0.826‡ [6.526]
Chems	10.48	19.12	0.527	12.66	15.83	0.774	0.764‡ [3.347]	0.639‡ [5.984]	Paper	9.539	18.67	0.490	8.671	16.92	0.489	0.417‡ [1.681]	0.682‡ [6.689]
Rubbr	10.66	19.75	0.520	11.55	17.61	0.633	0.619‡ [2.249]	0.766‡ [7.587]	Boxes	12.54	21.43	0.567	15.96	18.00	0.864	1.025‡ [3.876]	0.680‡ [6.702]
Txtls	7.518	23.18	0.307	13.59	17.46	0.756	0.860‡ [3.101]	0.608‡ [4.871]	Trans	9.925	18.72	0.509	11.92	16.88	0.683	0.676‡ [2.732]	0.708‡ [6.922]
BldMt	10.40	20.10	0.498	10.67	17.03	0.603	0.564‡ [2.172]	0.764‡ [7.555]	Whlsl	8.753	17.64	0.474	9.961	15.86	0.603	0.495‡ [2.276]	0.746‡ [7.764]
Cnstr	11.47	24.03	0.461	13.17	20.28	0.630	0.753‡ [2.437]	0.768‡ [6.498]	Rtail	12.12	19.57	0.599	14.65	17.90	0.797	0.841‡ [3.484]	0.847‡ [8.290]
Steel	9.013	27.69	0.311	14.37	22.55	0.620	0.770‡ [2.759]	0.955‡ [8.073]	Meals	11.42	18.41	0.598	13.09	16.33	0.777	0.774‡ [3.573]	0.706‡ [8.359]
FabPr	3.672	24.65	0.133	12.66	16.96	0.723	0.839‡ [2.932]	0.482‡ [5.357]	Banks	11.87	20.54	0.559	13.62	17.57	0.753	0.801‡ [3.133]	0.744‡ [7.685]
Mach	10.22	22.59	0.435	12.29	18.57	0.641	0.651‡ [2.457]	0.834‡ [8.169]	Insur	11.62	18.63	0.603	11.54	16.16	0.689	0.666‡ [2.702]	0.658‡ [7.643]
ElcEq	14.05	21.99	0.621	14.97	19.89	0.737	0.811‡ [3.552]	0.972‡ [8.801]	RlEst	-0.583	20.84	-0.047	5.535	14.40	0.357	0.299 [1.201]	0.362‡ [4.751]
Autos	6.627	24.47	0.255	12.83	19.45	0.640	0.731‡ [3.251]	0.755‡ [7.020]	Fin	13.45	23.13	0.564	13.47	20.88	0.626	0.648‡ [2.647]	1.059‡ [9.192]
Aero	12.11	21.72	0.539	12.37	19.74	0.606	0.670‡ [2.347]	0.804‡ [7.485]	Other	5.757	22.67	0.236	9.468	18.61	0.488	0.474† [1.636]	0.703‡ [5.874]
Ships	8.367	23.60	0.338	11.04	19.67	0.541	0.637‡ [2.027]	0.633‡ [4.936]									

Notes: Economic significance results are reported for all industries over January 1979-December 2008 period. Means and standard deviations are reported as annualized percentages. "S.R." denotes Sharpe ratio in this table. Results for the oil strategy are based on updated parameter estimates of the rolling regression in equation (1): $r_t^i = \mu_i + \alpha_i r_{t-1}^{oil,spot} + \varepsilon_t^i$, starting from January 1979. Sample size is 60 observations, and we roll the sample window forward, one month at a time, while keeping the window's length fixed. $\hat{\alpha}$ and $\hat{\beta}$ are estimated using regression equation (6): $r_t^{os} - r_t^f = \alpha_i + \beta_i(r_t^m - r_t^f) + \varepsilon_t$. Here, r_t^{os} represents returns to oil strategy, r_t^m represents market returns, and r_t^f is the risk free rate. We use S&P500 returns as market returns proxy and 1-month T-Bill rate series as risk free rate proxy. Reported $\hat{\alpha}$ values are in annual percentages. Reported t-statistics are based on Newey-West HAC consistent standard errors for West Texas Intermediate oil spot price series and appear in square brackets. ‡, and † denote rejection of the null hypothesis that the parameter equals zero at the 5%, and 10% significance levels, respectively.

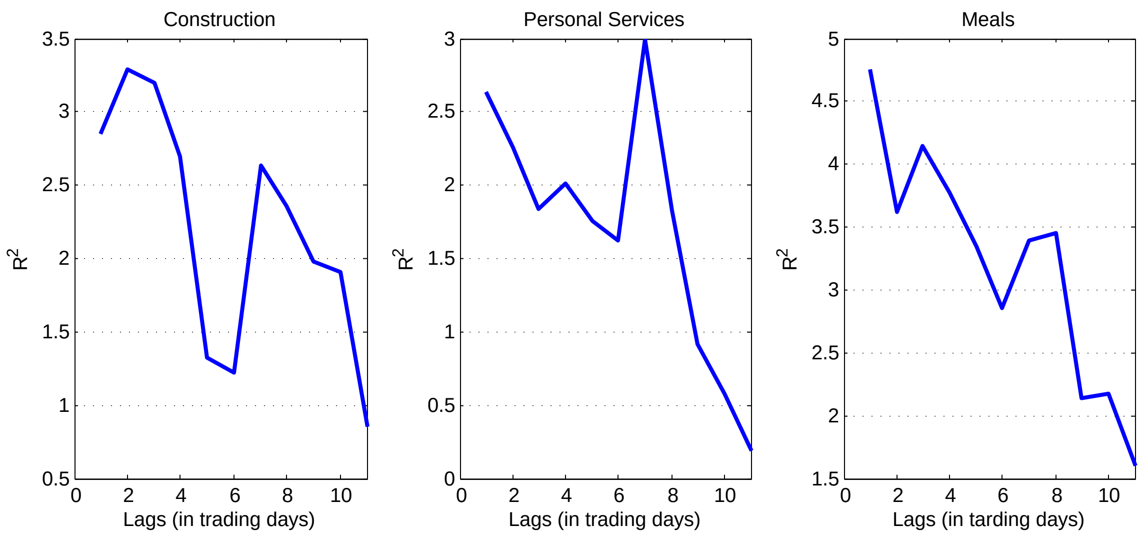
Table 8: Correlations between West Texas Intermediate spot oil price changes and some U.S. economic variables.

U.S. Economic Variables	Spot Oil Price	Oil Future Price
Default Spread	0.18	0.00
Term Structure	-0.02	0.05
Dividend Yield	-0.09	-0.07
Interest Rate	0.00	-0.07

The sample period is January 1983 to January 2009. The sampling frequency is monthly. Default spread is defined as the difference between Aaa and Baa corporate bond interest rates, rated by Moody's. The term structure is defined as the difference between the 10-year US Treasury bond and the 3-month US Treasury Bill rates. The interest rate is the 3-month US Treasury Bill rate. Dividend yields are from Thomson Datastream US market index series. Source: St. Louis Fed and Thomson Datastream.

8 Figures

Figure 1: Explanatory Power: Lagged Oil Returns



The figure depicts the R^2 of regression equation $r_t^i = \mu_i + \alpha_i r_{t-j}^{oil} + \varepsilon_t^i$ with different lag sizes in trading days, j, for West Texas Intermediate spot price changes and three industries: construction, personal services, and meals.